

# Decomposition, Reformulation, and Diving in University Course Timetabling

Edmund K. Burke, Jakub Mareček, Andrew J. Parkes

*School of Computer Science, University of Nottingham  
Jubilee Campus, Nottingham NG8 1BB, UK*

Hana Rudová

*Masaryk University Faculty of Informatics  
Botanická 68a, Brno 602 00, The Czech Republic*

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## Abstract

In many real-life optimisation problems, there are multiple interacting components in a solution. For example, different components might specify assignments to different kinds of resource. Often, each component is associated with different sets of soft constraints, and so with different measures of soft constraint violation. The goal is then to minimise a linear combination of such measures. This paper studies an approach to such problems, which can be thought of as multiphase exploitation of multiple objective-/value-restricted submodels. In this approach, only one computationally difficult component of a problem and the associated subset of objectives is considered at first. This produces partial solutions, which define interesting neighbourhoods in the search space of the complete problem. Often, it is possible to pick the initial component so that variable aggregation can be performed at the first stage, and the neighbourhoods to be explored next are guaranteed to contain feasible solutions. Using integer programming, it is then easy to implement heuristics producing solutions with bounds on their quality.

Our study is performed on a university course timetabling problem used in the 2007 International Timetabling Competition, also known as the Udine Course Timetabling Problem. The goal is to find an assignment of events to periods and rooms, so that the assignment of events to periods is a feasible bounded colouring of an associated conflict graph and the linear combination of the numbers of violations of four soft constraints is minimised. In the proposed heuristic, an objective-restricted neighbourhood generator produces assignments of periods to events, with decreasing numbers of violations of two period-related soft constraints. Those are relaxed into assignments of events to days, which define neighbourhoods that are easier to search with respect to all four soft constraints. Integer programming formulations for all subproblems are given and evaluated using ILOG CPLEX 11. The wider applicability of this approach is analysed and discussed.

## 1 Introduction

### 1.1 Motivation

There has recently been considerable progress in the development of mixed integer programming solvers (Nemhauser and Wolsey, 1988; Johnson et al., 2000; Bixby et al., 2004). To a considerable extent, this progress is due to the introduction of new primal and improvement heuristics (Fischetti and Lodi, 2003; Fischetti et al., 2005; Danna et al., 2005; Berthold, 2007a). These methods can be said to “dive” into a particular region of the search space in order to explore it intensely. This is intended to restrict and simplify the search space so that the sub-instance is easier to solve. Currently, diving heuristics are run only once the initial linear programming relaxation is solved: Polynomial-time reduction strategies (Lin, 1965) use the relaxed solution to identify a subset of variables whose values should be fixed. Typically, and inevitably, the dive will remove the optimal solutions; the optimum of the reduced instance is not necessarily optimal in the original instance. It is hoped, nevertheless, that improving integer feasible solutions can still be extracted from solutions of the modified instance. Despite substantial recent progress, we believe that there is still considerable scope for further work in this general direction.

The approach we propose is based on the observation that there is a complex structure to many real-world problems. The objective function is usually highly structured in itself, and hence not best thought of as the generic  $c^T x$  form, which is the usual starting point of theoretical analyses. In many instances, the overall objective function is a linear combination of many disparate terms with each term representing a total penalty for some unwanted structure within a possibly small part of a solution, or profit from some desirable structure. Furthermore, the different terms in the objective are rarely equally hard to handle. Some can be relatively easy, but some terms can be troublesome; representing them can require a large number of auxiliary variables. For example, some term might well contain a penalty that uses a “sum of absolute values” or “max of a max” structure that can require many extra variables to compute. Hence, the first ingredient of our approach is to generate sub-instances by selectively keeping some terms in the objective. Which terms should be kept in the objective, will become clearer once we sketch out the rest of our approach.

The second ingredient is the aggregation of variables: Defining a new variable to be some linear or simple non-linear function of existing variables, such as the maximum of a small subset. In many cases, a human expert inspecting the sub-instance would suggest that particular aggregations of variables would allow it to be rewritten into a form that is much easier to solve. Current diving heuristics, however, do not perform any aggregations that are specific to the diving, despite the potential to greatly reduce the number of variables and, furthermore, to do so in a manner that is quite different than reductions by means of fixing values of variables. We distinguish different potential intended usages of aggregation as follows:

- **Equivalence-based.** The new variable is ‘logically equivalent to the old variables’ in the sense that it can be used to replace them, and still preserve optimality and validity. This is the type of aggregation that is performed in preprocessing.
- **Validity-based.** The new aggregate variable is not intended to replace the old variables fully: They either supplement the original ones, or can be used to provide valid cuts and valid lower bounds.
- **Solution-based.** The new aggregate variable is not intended to replace the old variables fully: They either supplement the original ones, or can be used to provide valid solutions (upper bounds). This, in a certain sense, can be thought of as the dual of validity-based aggregation.

This concept of validity-based aggregation underlies many of the constructions in this paper.

Finally, current diving heuristics seem to have linear programming relaxation as the input and (possibly) an integer feasible solution as the output. We suggest a different approach, (possibly) producing integer feasible solutions together with lower bounds for the original instance, without utilising its linear programming relaxation. This makes it possible to run the diving heuristic prior to computing the first linear programming relaxation of the original instance and improve the performance of subsequent cut generation. In step one of our approach, a much smaller (“surface”) instance of integer programming is derived by picking suitable components of the original instance and applying the validity-based aggregation introduced above. By solving this instance, we obtain a valid lower bound for the original instance, in addition to a feasible input to the second step. In step two, we dive into a neighbourhood obtained by reducing the feasible solution of step one. Notice that the (“dive”) neighbourhood can often be much smaller compared to the original search space, whilst still being guaranteed to contain a feasible solution to the original instance. Various strategies can be used to control the order of performing the individual dives. In the long run, it would make sense to explore the possibilities of applying various strategies to initialise and perform dives, automating the choice of an aggre-

Offers / Model	Monolithic	Surface	Dive
Lower bounds	✓	✓	
Upper bounds	✓		✓
Completeness	✓		

Fig. 1. A schematic overview of the suggested decomposition: As a primal heuristic for the convergent monolithic model, we employ an aggregated surface model and a series of dives, bounded by the solution obtained at surface.

gating reduction strategy, as well as of tailoring automated reformulations better to instances obtained in such reduction strategies.

## 1.2 The Result

In this paper, we make an initial step in this direction, giving a “proof of concept” implementation for a particular class of instances from timetabling. In step one of our approach, a much smaller instance of integer programming is solved. Feasible solutions of the smaller instance define the neighbourhoods to dive into in step two. The smaller instance is derived using the “validity-based aggregation”, introduced above. We also hint at the power of so-far-non-automated reformulations on instances obtained using such reduction strategies.

In particular, we propose such a heuristic decomposition for Udine Course Timetabling, a benchmark course timetabling problem, used in Track 3 of the International Timetabling Competition 2007 ([Di Gaspero and Schaerf, 2006](#)). There, as in many other timetabling problems, feasible solutions are determined by a bounded graph colouring component ([Welsh and Powell, 1967](#); [Burke et al., 2004](#)), more specifically by an extension of a pre-colouring bounded in the number of uses of a colour, which is difficult in its own right ([Even et al., 1976](#); [Garey and Johnson, 1979](#); [Bodlaender and Fomin, 2005](#)). The quality of feasible solutions is measured by the number of violations of four additional complex soft constraints. These soft constraints place emphasis on:

- suitability of rooms with respect to their capacities
- suitability of the spread of the events of a course within the weekly timetable
- minimisation of the number of distinct rooms each course uses
- desirability of various patterns in distinct individual daily timetables.

Note that the latter three soft constraints will be formulated using the max

function. Modelling of the soft constraints, as opposed to the bounded graph colouring component on its own, entails an increase in the dimensions of the model, and consequently of the run-time, making even modest real-life instances difficult to solve using a stand-alone integer programming solver (Burke et al., 2008b, 2007), or branch-and-cut procedures (Avella and Vasil'ev, 2005; Burke et al., 2008a).

Hence, we propose a heuristic that decomposes the process of solving the instance into two stages, which are outlined in Table 1. The “surface” stage is restricted to the bounded colouring problem with the two period-related soft constraints. The “dives” fix certain features of the solution found at the surface, and produce a locally optimal solution to the complete instance. We employ two “control strategies” for executing the dives. In “anytime strategies”, dives are executed whenever a feasible bounded colouring is found at the surface. In “contract strategies”, a time limit for the search at the surface is given, and dives are executed only afterwards. As it seems, previously underutilised “contract strategies” with multiple “neighbourhoods” searched in the dives in a suitable order perform considerably better than the traditional anytime strategies using a single type of restriction.

A solver based on this approach was implemented using ILOG Concert and ILOG CPLEX 11. Using non-automatically reduced integer programming formulations, it yields good solutions to instances of up to 434 events and 81 distinct enrolments (“curricula”) within thirty minutes of run time on a desktop PC. The lower bounds obtained at the surface are better than those which Lach and Lübbecke (2008a) obtain within the same time limits. Overall, the heuristic produces solutions for the Udine Course Timetabling Problem, together with bounds on their distance from optimality.

The two-fold aims of this paper are reflected in its structure. The immediate goal is to obtain better solutions and lower bounds to the Udine Course Timetabling problem. The problem is introduced in Section 2. The particular heuristic is outlined in Section 4. The integer programming formulations of the subproblems we employ are presented in Section 5. Finally, computational experience is described in Section 7. We regard this as part of a longer-term goal, however, which is the development of methods to better control and exploit various, possibly automated, decompositions and reformulations. The methodology of “Multiphase Exploitation of Multiple Objective-/value-restricted Submodels” (or “MEMOS” for short) is outlined in Section 3. We are not claiming that any of the individual techniques presented in Section 3 are novel *per se*. Rather, we are providing a basis for a rationalisation and classification of previously known methods, which are surveyed in Section 6. Both the particular solver and the more generally applicable approach to the design of hybrid metaheuristics for complex problems may be of separate interest.

## 2 Problem Description

### 2.1 University Course Timetabling

In general, timetabling problems share the search for feasible colourings of conflict graphs, where vertices represent events and there is an edge between two vertices if the corresponding events cannot take place at the same time (Burke et al., 2004). This graph colouring component is often bounded in the number of uses of a colour and has to provide an extension of pre-coloured conflict graph, such that the total number of violations of certain soft constraints is minimised. In university course timetabling (Bardadym, 1996; Burke et al., 1997; Petrovic and Burke, 2004; McCollum, 2007), these soft constraints often stipulate that events should be timetabled for rooms of appropriate sizes. At least or at most a certain number of days of instructions should be timetabled for groups of students and individual teachers, and daily timetables of students or teachers should not exhibit particular patterns. For example, a single event per day or long gaps in a daily timetable, or on the other hand, six events per day with no gap around lunch time may be deemed undesirable. The particulars of each problem instance vary widely from university to university, and a number of both exact and heuristic search methods have been attempted on a range of instances. For surveys, see Carter and Laporte (1998); Schaerf (1999); Burke and Petrovic (2002). Out of the numerous variations of the problem in use, instances from the University of Udine (Di Gaspero and Schaerf, 2003) and Purdue University (Rudová and Murray, 2003; Murray et al., 2007), together with random problem instances used in the International Timetabling Competition<sup>1</sup> in 2002 and 2007 have recently started to be considered as benchmark problems.

### 2.2 The Udine Course Timetabling Problem

The Udine Course Timetabling problem studied in this paper is maintained by Di Gaspero and Schaerf (2003) at *Università degli studi di Udine*. There are two important assumptions:

- Events are partitioned into disjoint subsets, called courses; events of any one course have to take place at different times, are attended by the same number of students, and are freely interchangeable

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<sup>1</sup> See Di Gaspero et al. (2007) or <http://www.cs.qub.ac.uk/itc2007/> for International Timetabling Competition (ITC) 2007 and <http://www.idsia.ch/Files/ttcomp2002/> for ITC 2002.



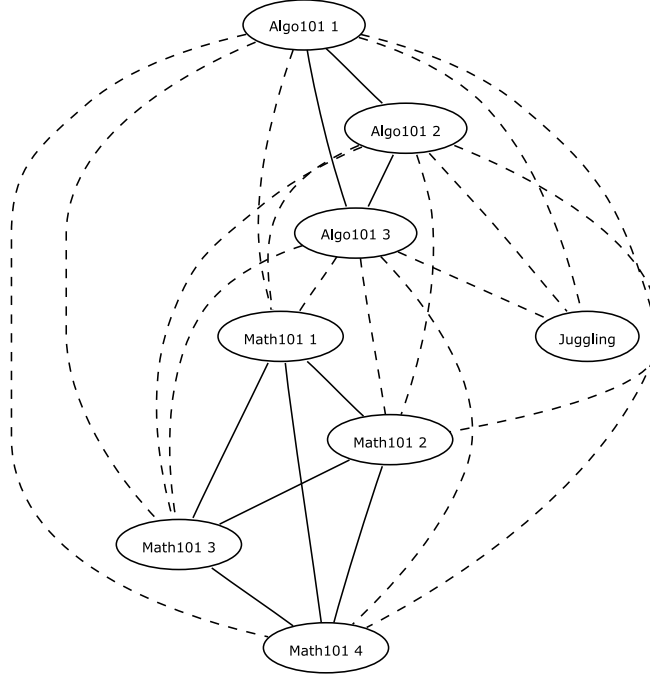


Fig. 2. The colouring component of a trivial instance of course timetabling: There are three courses, Juggling, Math101 and Algo101, with 1, 4 and 3 events respectively. One group of students attends both Math101 and Algo101, another group attends both Juggling and Algo101, and events attended by a group of students cannot overlap in time. Each vertex in the associated conflict graph represents an event and there is an edge between two vertices, if the two corresponding events cannot take place concurrently. The edge is dashed, if this requirement is given by the enrolment of a student in both courses.

- A small number of distinct, possibly overlapping, sets of courses, representing enrolments prescribed to various groups of students, are identified and referred to as curricula.

Due to the second assumption, this problem is often referred to as “curriculum based timetabling”, as opposed to “student enrolment based timetabling”, which tries to minimise the number of conflicts among a possibly large number of enrolments. See Figure 2 for an illustrative example. The complete input can be captured by seven constant sets and eight mappings:

- $C, U, T, R, D, P$  are sets of courses, curricula, teachers, rooms, days, and periods, respectively
- $\tilde{U}^u$  is the non-empty set of courses in curriculum  $u$
- $N$  is a subset of  $C \times P$ , giving forbidden course-period combinations
- $E^c$  is the number of events course  $c$  has in a week
- $S^c$  is the number of students enrolled in course  $c$
- $Q^c$  is the prescribed minimum number of distinct week-days of instruc-

- $\tilde{T}^t$  is the subset of courses  $C$  taught by teacher  $t$
- $A^r$  is the capacity of room  $r$
- $\tilde{D}^d$  is the subtuple (ordered subset) of  $P$  corresponding to periods in day  $d$
- $W$  is a vector of non-negative weights ( $W^{\text{RCap}}, W^{\text{TSpr}}, W^{\text{TCom}}, W^{\text{RStb}}$ ) for the four soft constraints described below.

Informally, the goal is to produce a mapping from events to period-rooms pairs such that:

- (1) For each course  $c$ ,  $E^c$  events are timetabled
- (2) No two events take place in the same room in the same period
- (3) No two events of a single course, no two events taught by a single teacher, and no two events included in a single curriculum are taught

Table 1

Instances of the Udine Course Timetabling problem: numbers of rooms and periods; the number of courses and the sum of their events in a week; frequency, or the portion of period-room slots in use, and utilisation, or the portion of period-seat slots in use (Beyrouthy et al., 2007); the number of distinct enrolments (“curricula”); numbers of edges and density in conflict graphs (CG) with vertices representing courses, rather than events (Burke et al., 2007).

Instance	AKA	Rooms	Periods	Courses	Events	Frequency (used slots)	Utilisation (used seats)	Curricula	Edges in CG (course-based)	Density of CG (course-based)
comp01	Fis0506-1	6	30	30	160	88.89 %	45.98 %	14	53	12.18 %
comp02	Ing0203-2	16	25	82	283	70.75 %	46.28 %	70	401	12.07 %
comp03	Ing0304-1	16	25	72	251	62.75 %	38.30 %	68	342	13.38 %
comp04	Ing0405-3	18	25	79	286	63.56 %	33.22 %	57	212	6.88 %
comp05	Let0405-1	9	36	54	152	46.91 %	43.50 %	139	917	64.08 %
comp06	Ing0506-1	18	25	108	361	80.22 %	45.28 %	70	437	7.56 %
comp07	Ing0607-2	20	25	131	434	86.80 %	41.71 %	77	508	5.97 %
comp08	Ing0607-3	18	25	86	324	72.00 %	37.39 %	61	214	5.85 %
comp09	Ing0304-3	18	25	76	279	62.00 %	32.67 %	75	251	8.81 %
comp10	Ing0405-2	18	25	115	370	82.22 %	36.38 %	67	481	7.34 %
comp11	Fis0506-2	5	45	30	162	72.00 %	56.23 %	13	75	17.24 %
comp12	Let0506-2	11	36	88	218	55.05 %	35.06 %	150	1181	30.85 %
comp13	Ing0506-3	19	25	82	308	64.84 %	38.14 %	66	216	6.50 %
comp14	Ing0708-1	17	25	85	275	64.71 %	34.78 %	60	368	10.31 %



at the same time

- (4) No event of course  $c$  is taught in a period  $p$ , if  $\langle c, p \rangle$  is in  $N$
- (5) The objective is to minimise a weighted sum of penalty terms

$$W^{\text{RCap}} P^{\text{RCap}} + P^{\text{TSpr}} W^{\text{TSpr}} + P^{\text{TCom}} W^{\text{TCom}} + P^{\text{RStb}} W^{\text{RStb}},$$

where:

- $P^{\text{RCap}}$  (for “room capacity”) is the number of students left without a seat at an event, summed across all events; this is the value of the number of students attending an event minus the capacity of the allocated room over all events where the value is positive
- $P^{\text{TSpr}}$  (for “spread of events of a course over distinct week-days”) sums the value of the number of prescribed distinct week-days of instruction minus the actual number of distinct week-days of instruction over all courses where the value is positive
- $P^{\text{TCom}}$  (for “time compactness”) is the number of isolated events in daily timetables of individual curricula; “[f]or a given curriculum we account for a violation every time there is one lecture not adjacent to any other lecture on the same day” (Di Gaspero et al., 2007)
- $P^{\text{RStb}}$  (for “room stability”) is the number of distinct course-room allocations on the top of a single course-room allocation per course.

In the original paper of [Di Gaspero and Schaerf \(2003\)](#), there were described only four instances of the Udine Course Timetabling Problem of up to 252 events and 57 distinct enrolments, with  $(W^{\text{RCap}}, W^{\text{TSpr}}, W^{\text{TCom}}, W^{\text{RStb}}) = (1, 5, 2, 0)$ . Fourteen more instances of up to 434 events and 81 distinct enrolments have now been made available in Track 3 of the International Timetabling Competition, with weights  $(W^{\text{RCap}}, W^{\text{TSpr}}, W^{\text{TCom}}, W^{\text{RStb}}) = (1, 5, 2, 1)$ . Their dimensions are summarised in Table 1.

### 2.3 An Integer Programming Formulation

Formally, the Udine Course Timetabling problem can be described using an integer programming model. Doing so necessitates the choice of decision variables. This is of little importance if the sole purpose is to formulate the problem formally, but becomes of paramount importance, if the performance of the formulation is evaluated. It seems tempting to see the problem as a variation of the three-index assignment and to use binary variables for each event-room-period combination. This corresponds to the trivial formulation of graph colouring, where the number of binary variables is the product of the number of vertices and an upper bound on the number of colours. There are, however, many alternative formulations of graph colouring ([Burke et al., 2007](#)) and it seems reasonable to use the best avail-

able formulation of graph colouring that would admit formulation of the soft constraints. After exploring a number of such alternatives, [Burke et al. \(2007\)](#) proposed a formulation based on a suitable clique-partition, which is given implicitly in many graph colouring applications. For Udine Course Timetabling, this formulation translates to a smaller number of “core” binary decision variables  $x$ , given by the product of the numbers periods, rooms, and courses, rather than events. Outside of those, there are dependent variables  $v$ ,  $q$ ,  $z$ , and  $y$ , whose values are derived from the values of  $x$  in the process of solving:

- $x$  are binary decision variables indexed with periods, rooms and courses. Their values are constrained so that in any feasible solution, course  $c$  should be taught in room  $r$  at period  $p$ , if and only if  $x_{p,r,c}$  is set to one.
- $v$  are binary decision variables indexed with courses and days. Their values are constrained so that in any feasible solution, there is at least one event of course  $c$  held on day  $d$ , if and only if  $v_{d,c}$  is set to one.
- $q$  are integer decision variables indexed with courses, whose values are bounded below by zero and above by the number of days in a week. Their values are constrained so that in any feasible solution,  $q_c$  is the number of days course  $c$  is short of the recommended days of instruction,  $Q^c$ .
- $z$  are binary decision variables indexed with curricula, days, and an index-set  $Z$  of natural pattern-penalising constraints. Their values are constrained so that in any feasible solution,  $z_{u,d,s}$  is set to one if and only if the pattern-penalising constraint indexed by  $s \in Z$  is violated in the timetable for curriculum  $u$  and day  $d$  given by the solution.
- $y$  are binary decision variables indexed with rooms and courses. Their values are constrained so that in any feasible solution,  $y_{r,c}$  is set to one if and only if room  $r$  is used by course  $c$ .

The objective function can be expressed as:

$$\begin{aligned} \min \quad & W^{\text{RCap}} \sum_{r \in R} \sum_{p \in P} \sum_{\substack{c \in C \\ S^c > A^r}} x_{p,r,c} (S^c - A^r) + W^{\text{TCom}} \sum_{u \in U} \sum_{d \in D} \sum_{s \in Z} z_{u,d,s} \\ & + W^{\text{TSpr}} \sum_{c \in C} q_c + W^{\text{RStb}} \sum_{c \in C} \left( \left( \sum_{r \in R} y_{r,c} \right) - 1 \right) \end{aligned}$$

Hard constraints can be formulated as follows:

$$\forall c \in C \quad \sum_{p \in P} \sum_{r \in R} x_{p,r,c} = E^c \quad (1)$$

$$\forall p \in P \forall r \in R \quad \sum_{c \in C} x_{p,r,c} \leq 1 \quad (2)$$

$$\forall p \in P \forall c \in C \quad \sum_{r \in R} x_{p,r,c} \leq 1 \quad (3)$$

$$\forall p \in P \forall t \in T \quad \sum_{r \in R} \sum_{c \in \tilde{T}^t} x_{p,r,c} \leq 1 \quad (4)$$

$$\forall p \in P \forall u \in U \quad \sum_{r \in R} \sum_{c \in \tilde{U}^u} x_{p,r,c} \leq 1 \quad (5)$$

$$\forall \langle c, p \rangle \in N \quad \sum_{r \in R} x_{p,r,c} = 0 \quad (6)$$

Constraint (1) enforces a given number of events to be taught for each course. Constraint (2) ensures no two events are taught in a single room at a single period. Constraints (3–5) stipulate that only one event within a single course or curriculum, or taught by a single teacher can be held at any given period. Notice the similarity of constraints (1–5) and the clique-based formulation of bounded graph colouring (Burke et al., 2007). Finally, constraint (6) forbids the use of some periods in timetables of some courses, corresponding to a pre-colouring extension. Notice also that constraint (5) renders constraint (3) redundant, if there are no courses outside of any curricula.

The formulation of soft constraints is less trivial and, as will be shown in Section 7 and Table 4, the formulation presented below proves to be quite challenging for modern general purpose integer programming solvers, even after the strengthening proposed by Burke et al. (2008a). Values of  $v$  are forced to maxima of certain subsets of  $x$  using constraints (7–8), in effect constructing daily timetables for individual curricula. Subsequently, the number of distinct week-days of instruction that course  $c$  is short of the prescribed value  $Q^c$ , can be forced into  $q_c$  using constraint (9):

$$\forall c \in C \forall d \in D \forall p \in \tilde{D}^d \quad \sum_{r \in R} x_{p,r,c} \leq v_{d,c} \quad (7)$$

$$\forall c \in C \forall d \in D \quad \sum_{r \in R} \sum_{p \in \tilde{D}^d} x_{p,r,c} \geq v_{d,c} \quad (8)$$

$$\forall c \in C \quad \sum_{d \in D} v_{d,c} \geq Q^c - q_c \quad (9)$$

The “natural” formulation of penalisation of patterns (Burke et al., 2008b) occurring in daily timetables of individual curricula goes through the daily timetables bit by bit, first by checking isolated events in the first and the

last period of the day, and later looking for triples of consecutive periods with only the middle period occupied by an event: For an instance with four periods per day, this is:

$$\forall u \in U, d \in D, \forall \langle p_1, p_2, p_3, p_4 \rangle \in \tilde{D}^d \sum_{c \in \tilde{U}^u} \sum_{r \in R} (x_{p_1, r, c} - x_{p_2, r, c}) \leq z_{u, d, 1} \quad (10)$$

$$\forall u \in U, d \in D, \forall \langle p_1, p_2, p_3, p_4 \rangle \in \tilde{D}^d \sum_{c \in \tilde{U}^u} \sum_{r \in R} (x_{p_4, r, c} - x_{p_3, r, c}) \leq z_{u, d, 2} \quad (11)$$

$$\forall u \in U, d \in D, \forall \langle p_1, p_2, p_3, p_4 \rangle \in \tilde{D}^d \sum_{c \in \tilde{U}^u} \sum_{r \in R} (x_{p_2, r, c} - x_{p_1, r, c} - x_{p_3, r, c}) \leq z_{u, d, 3} \quad (12)$$

$$\forall u \in U, d \in D, \forall \langle p_1, p_2, p_3, p_4 \rangle \in \tilde{D}^d \sum_{c \in \tilde{U}^u} \sum_{r \in R} (x_{p_3, r, c} - x_{p_2, r, c} - x_{p_4, r, c}) \leq z_{u, d, 4} \quad (13)$$

Just as for constraints (7–9), cuts strengthening constraints (10–13) were described by [Burke et al. \(2008a\)](#). Finally, values of  $y$ , similar to values of  $v$ , are forced to maxima of certain subsets of  $x$ :

$$\forall p \in P \forall r \in R \forall c \in C \quad x_{p, r, c} \leq y_{r, c} \quad (14)$$

$$\forall r \in R \forall c \in C \quad \sum_{p \in P} x_{p, r, c} \geq y_{r, c} \quad (15)$$

These constraints complete the formulation, which will be later referred to as **Monolithic**.

## 2.4 How Difficult is this for Exact Solvers?

One might hope that it is enough to pass this formulation to a modern integer programming solver and wait. After all, integer programming has been used in timetabling ever since [Lawrie \(1969\)](#) generated feasible solutions to a school timetabling problem using a branch and bound procedure with Gomory cuts. [Tripathy \(1984\)](#) and [Carter \(1989\)](#) solved instances of a course timetabling problem of up to 287 events with several soft constraints using Lagrangian relaxation. They have not, however, introduced any constraints penalising interaction between events in timetables other than, of course, straightforward conflicts. More recently, a number of modest instances of course timetabling problems have been tackled using off-the-shelf solvers, without introducing any new cuts ([Dimopoulou and Miliotis, 2004](#); [Qualizza and Serafini, 2005](#); [Daskalaki et al., 2004, 2005](#); [Mirhasani, 2006](#)). For instance, [Daskalaki et al. \(2004, 2005\)](#) solved instances of

up to 211 events using ILOG CPLEX. Of special interest are studies by [Al-Yakoob and Sherali \(2007\)](#) and [Schimmelpfeng and Helber \(2007\)](#), who have modelled a larger number of constraints. In the most rigorous study so far, [Avella and Vasil'ev \(2005\)](#) presented a branch-and-cut solver for the Benevento Course Timetabling Problem, which forbids some interactions of events in timetables other than conflicts using hard constraints. In this setting, [Avella and Vasil'ev \(2005\)](#) have been able to solve instances of up to 233 events and 14 distinct enrolments, but conceded that application of their solver to the four small instances of Udine Course Timetabling available in 2005 yielded “poor results”. In Udine Course Timetabling, such interactions are penalised by soft constraints (7–15), which (it turns out) make the problem considerably more difficult. Several integer programming formulations of the problem have been studied by [Burke et al. \(2007, 2008b\)](#), and more recently by [Lach and Lübbecke \(2008a,b\)](#). Both approaches can now solve the original instances of Udine Course Timetabling from 2005, but optimal solutions to instances from the International Timetabling Competition 2007, or optima for large real-life instances of university course timetabling problems are, as it seems, out of reach, so far.

In particular, it seems that it is the run-time of the linear programming (LP) solver that is prohibitive to progress on more difficult instances from the International Timetabling Competition (ITC) using the **Monolithic** formulation. For relatively easier instances (comp01 and comp11 from ITC 2007), root relaxation obtained from **Monolithic** takes less than thirty seconds to solve using the default ILOG CPLEX 11 Dual Simplex LP Solver and the search proceeds swiftly. On the remaining instances, however, the root relaxation is far more expensive, taking up to 6489 seconds on comp07. For complete results obtained using the CPLEX 11 Dual Simplex LP Solver, see Table 4. Informal evidence suggests that run times of both the CPLEX 11 Barrier and the CPLEX 11 Primal Simplex LP solvers are shorter, whereas run-times of either SoPlex ([Wunderling, 1996](#)) and CLP ([Forrest et al., 2004](#)) are longer. Hence, it is not particularly surprising that for most instances (all except from comp01, comp05, and comp11), CPLEX Mixed Integer Programming (MIP) solver using **Monolithic** and default settings does not produce any feasible solution within 40 CPU units, branching at the speed of ten to thirty nodes per hour. This can hardly be described as satisfactory progress.

Although the total run-time or time spent at the root node may not be of particular importance, as long as the instance is solved close to optimality within a reasonable time limit, for example over a weekend, relying on robustness of modern solvers does not seem to be an option for real-life instances ([Murray et al., 2007](#)). First, such instances are often many times larger than those used in the International Timetabling Competition 2007, including comp07. Second, their formulations are considerably more com-

plex and tend to change over time, whereas the behaviour of general solvers on monolithic formulations tends to be rather difficult to predict, with run-time often rising rapidly on addition of seemingly trivial constraints. Finally, general solvers only seldom perform in the “anytime” fashion of [Zilberstein \(1996\)](#) on monolithic formulations, which would make it possible to obtain a solution whenever the solver is stopped. It thus makes sense to study decompositions of the problem and the performance of heuristic methods based on them.

### 3 Multiphase Exploitation of Multiple Objective-/Value-restricted Sub-models (MEMOS)

In short, our approach can be seen as a hybridisation of loosely coupled integer programming solvers working on very different sub-problems of similar difficulty. Each solver is, time-limit permitting, exact within the given search space, and together, the solvers provide heuristic solutions with global lower bounds. It seems, however, useful to set this description in the broader context of hybrid metaheuristics, even if this still seems difficult to do precisely, but concisely, despite the numerous attempts ([Calégari et al., 1999](#); [Puchinger and Raidl, 2005](#); [El-Abd and Kamel, 2005](#); [Raidl, 2006](#)) to develop a taxonomy of the field.

#### 3.1 Hybridisation

Hybridisation can clearly occur in two different fashions:

- Algorithm hybridisation, using multiple algorithms for the same problem
- Formulation hybridisation, using multiple subproblems or multiple levels of abstraction

Although, in theory, hybridisation can occur in both fashions, in practice, heuristics often exploit only algorithm hybridisation: Multiple algorithms producing solutions to the complete problem, with or without a feasible solution on the input. A typical example of algorithm hybridisation is the “construct-improve” scheme, which is a standard practice in metaheuristic solvers. A constructive algorithm is used in order to produce one, or many, different initial solutions, which are then improved using some variant of local search. See the concise overview by [Blum and Roli \(2003\)](#) for details. Embedding of multiple primal and improvement heuristics ([Fischetti and Lodi, 2003](#); [Danna et al., 2005](#); [Berthold, 2007b](#)) in general integer program-



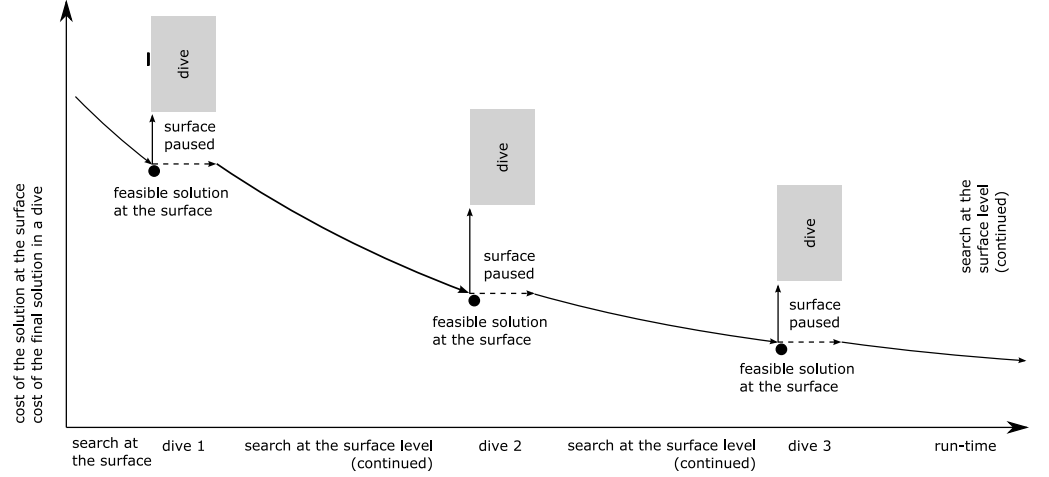


Fig. 3. A schematic illustration of the data flows in the metaheuristic.

ming solvers can be seen as another example of algorithm hybridisation. In contrast, the deliberate creation and exploitation of multiple sub-problems, restricted to certain components in the objective function, with certain values fixed, or both, seems underutilised.

### 3.2 Submodels

The critical point in our approach is precisely that: sub-problems solved at various stages are different, although possibly overlapping. That is, we create sub-problems using combinations of

- **Value-Restrictions:** Fix the values of a subset of the variables, distance from a solution with respect to Hamming distance ( $L_0$  norm), or sums across subsets of variables. This is a standard method to generate a neigh-

bourhood.

- **Objective-Restrictions:** Suppose that we have a minimisation problem and some penalty term  $P^R$  is part of the objective, with associated weight  $W^R$ . We then use one of two options:

- **Objective-Ignore-Term** We drop all consideration of the penalty – this corresponds to setting  $W^R = 0$ .
- **Objective-Fix-Term** We force  $P^R = 0$ . This converts the penalty to a hard constraint.

The objective restriction might loosely be thought of as the dual of the variable restrictions.

In any case, the intent is that the restriction will give a sub-problem that can be significantly simplified compared to the full problem, and of comparable difficulty to other problems obtained in the decomposition.

This can be illustrated on a class of problems, which often occurs in Scheduling and Timetabling applications, where there is a graph colouring component expanded over another dimension. Imagine for example the assignment of jobs to time-periods, expanded over machines, or the assignment of events to time-periods, expanded over rooms. In such cases, only one part of the objective is usually related to the expanded problem, whereas the rest is related to the graph colouring component. This results in structures such as:

$$\min \left( \sum_{i=1}^n c_i x_i + \sum_{j=1}^o d_j \max_{k \in I_j} x_k + \sum_{l=o+1}^p d_l \max(f(l, \max_{m \in I_l} x_m), 0) \right) \quad (16)$$

$$\max_{k \in I_j} x_k \leq 1 \quad \forall j \in \{1, 2, \dots, o\} \quad (17)$$

$$Ax \geq b \quad (18)$$

$$x \in \{0, 1\}^n \quad (19)$$

where  $n$ ,  $m$ ,  $o$ , and  $p$  are integral constants,  $x$  is a vector of  $n$  integral decision variables,  $A$  is an  $n \times m$  constant matrix,  $b$ ,  $c$ , and  $d$  are compatible constant vectors, and for each  $j = \{1, 2, \dots, p\}$ ,  $I_j$  is a subset of  $\{1, 2, \dots, n\}$ . Notice that the second two terms in the objective function, weighted by  $d$ , are related only to the graph colouring component, and necessitate implementation of the  $\max$  function using additional variables. The number of “core” variables  $x$  can be much less than the number of additional variables implementing the  $\max$  function over various subsets of  $x$ . Hence, it makes sense to use the restricted objective:

$$\min \left( \sum_{j=1}^o d_j \max_{k \in I_j} x_k + \sum_{l=o+1}^p d_l \max(f(l, \max_{m \in I_l} x_m), 0) \right), \quad (20)$$

ignoring the first term in the original objective (16). Given the constraint matrix  $A$  exhibit certain structure (17), this should allow for aggregation of  $n$  variables  $x$  into  $o$  variables  $y$ :

$$\min \left( \sum_{j=1}^o d_j y_j + \sum_{l=o+1}^p d_l \max(f(l, y_{g(l)}), 0) \right) A'y \geq b' \quad (21)$$

$$y \in \{0, 1\}^o \quad (22)$$

where  $g$  is a suitable mapping. Notice that some constraints may have to be relaxed in deriving the new constraints  $(A'b')$  from the original ones  $(Ab)$ . In Table 1 and below, we denote such a subproblem as “surface”. Such an objective-restricted subproblem, however, should solve considerably faster than the original problem (16–19).

Once a solution to the objective-restricted subproblem is found, it makes sense to resolve the original problem (16–19) with the additional constraints:

$$\max_{k \in I_j} x_k = y_j \quad \forall j \in \{1, 2, \dots, o\} \quad (23)$$

$$\max_{m \in J_l} (f(l, \max_{m \in J_l} x_m)) = y_l \quad \forall l \in \{o+1, o+2, \dots, p\}. \quad (24)$$

In Table 1 and below, we denote such subproblems as “dives”. This should result in considerable reductions of the model in presolving, and consequently in value-restricted subproblems which solve considerably faster than the original problem (16–19).

One can also use any combination of these, and could also separately treat different terms of the objective. This is, however, limited by the availability of a decomposition into such sub-problems, given by the structure of a solution and the objective, applicable reformulations, and our ability to automate their execution. For many “academic” problems there tends to be just a single term on the objective – for example, for the TSP we have only the tour length, and the objective restriction is hence not relevant. For many real-life problems, however, it is quite likely that the solution has a more complex structure, and there are multiple soft constraints corresponding to multiple penalty terms in the objective. University course timetabling (Murray et al., 2007) as opposed to pure graph colouring, or vehicle routing problems (Chabrier, 2006; Pisinger and Røpke, 2007) as opposed to the travelling salesman problem, provide good examples of possible application areas. In this case ignoring or fixing some terms can give significantly easier problems, yet still provide enough information to guide solution of the full problem. As we will see, automated preprocessing in-built in modern integer programming solvers is often too weak, and we do need to apply non-automatic reformulations “by-hand”. Ultimately, our work is directed towards automating decompositions and reformations of such problems

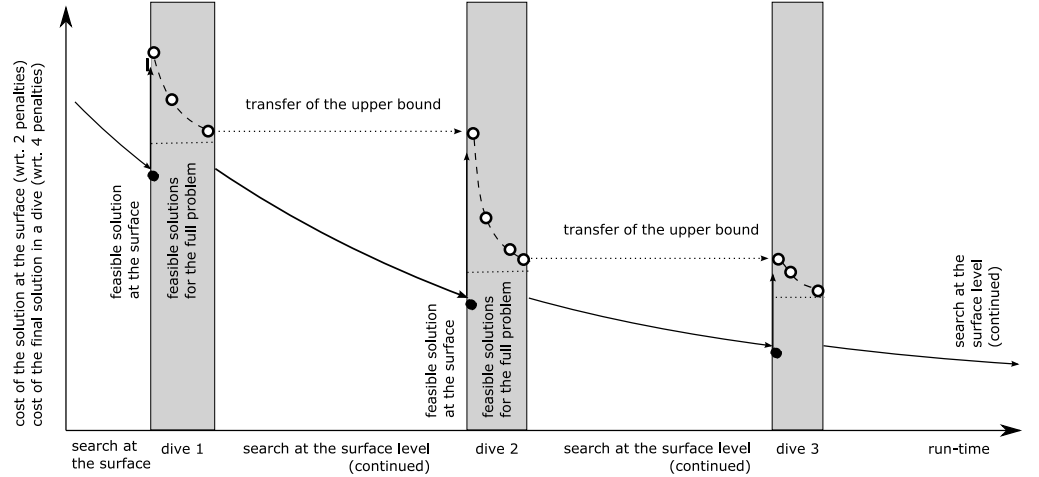


Fig. 4. A schematic illustration of information flows in the anytime algorithm: feasible solutions at the surface are transformed into neighbourhoods for dives, executed immediately. Upper bounds (costs of best-so-far solutions) are being carried over from dive to dive.

with “multiple soft constraints”, exploiting cases in which the objectives can have differing levels of importance.

### 3.3 Control Strategies

Another important and often neglected question in the design of hybrid metaheuristics asks for the sequence of periods of searching at the surface and periods of diving in neighbourhoods, sometimes referred to as “the control strategy” (Puchinger and Raidl, 2005; Raidl, 2006). Very often, a variant of the anytime algorithm (Zilberstein, 1996) is used, perhaps because it fits well into the large neighbourhood search scheme. There are,

however, two obvious alternatives of the producer-consumer relationship:

- **Anytime** algorithm: search at the surface and dives are interleaved and dives are performed as soon as suitable feasible solutions are found. The algorithm is parametrised with the types of dives performed, their order, and possibly the onset of execution of each type. See also Figure 4.
- **Contract** algorithm: search at the surface is carried out for a certain time and only then are the dives performed, firstly ordered by dive type with the least expensive dives coming first, and secondly ordered in the ascending order of the cost (in minimisation problems) of the solution at the surface the dive is derived from. Hence, the algorithm is parametrised with the types of dives performed, the time limit and the proportion of the time limit spent at the surface. See also Figure 5.

It seems that, in practice, a time-limit is often given and considerable performance improvements can be gained from exploiting this in a **Contract** algorithm. If the neighbourhoods can be searched in the ascending order of the cost of the solution at the surface and the cost of the present-best solution found in dives is applied as an upper bound in all dives except the first one, a considerable number of dives can be cut off immediately and the algorithm needs not to be parametrised with the onset of diving. (This is suggested in Figure 5.) Notice that the ascending order of the cost corresponds to the inverse order of the time of discovery, if we are producing only progressively improving solutions at the surface.

Generally, such Multiphase Exploitation of Multiple Objective-/value-restricted Submodels (MEMOS) will no longer be complete or exact. The intention is, however, to produce good solutions quickly.

## 4 MEMOS for Udine Course Timetabling

In the design of the particular MEMOS heuristic, we need to make specific decisions as to which sub-problems the “surface” and “dive” components need to solve. In doing so, it seems useful to think of the problem from the multi-objective perspective. In the Udine Course Timetabling problem introduced in Section 2, a given set of weights is used to linearise the penalties given by the number of violations of four soft constraint (“objectives”) into a single-objective problem. The four objectives are not necessarily linked, however. The formulation introduced in Section 2.3 models the four soft constraints one-by-one, each objective using a separate subset of constraints and a separate subset of variables derived from the main decision variables. Hence, it is natural to consider sub-problems arising from setting weights related to a subset of the four soft constraints to zero.

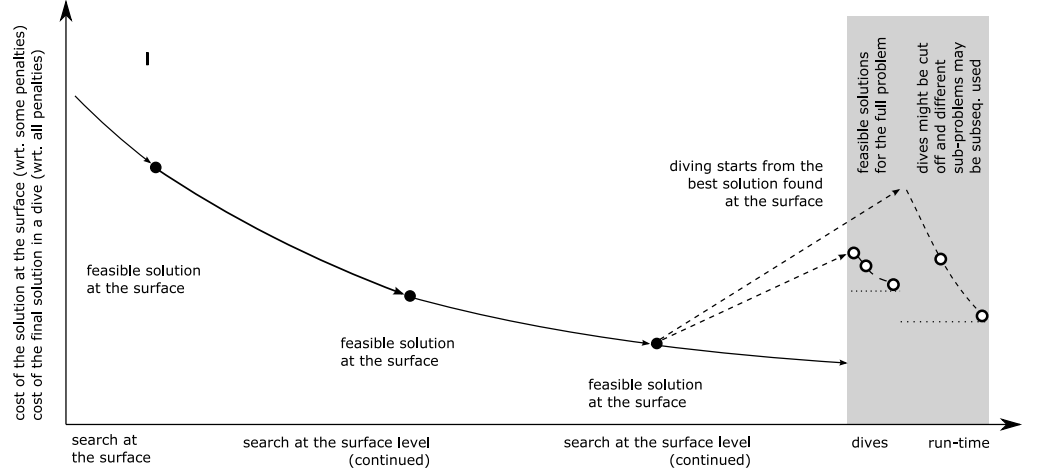


Fig. 5. A schematic illustration of the contract algorithm: dives of all types are postponed until the surface search finishes (runs out of time), when they are carried out in the descending order of the time of discovery of the neighbourhood, with the upper bound found from in the best neighbourhood often cutting off the dives into other neighbourhoods as soon as their local lower bounds are established.

If some weights are set to zero, the corresponding objective can be ignored and the problem formulation can be simplified. Ideally, one would be able to rely upon the preprocessing in-built in an integer programming solver to do this. As suggested by Table 2, however, present-day general purpose integer programming solvers are not particularly effective for such major reformulations. Non-automatic reformulation can, however, result in much faster relaxations, outside of having other desirable properties (Trick, 2005). In our case, such a desirable property might be the ease of conversion of solutions obtained at the “surface” to neighbourhoods for the dives. As suggested in Table 4, a careful choice of the decomposition and manual reformulation can lead to the run-time of the linear programming solver at



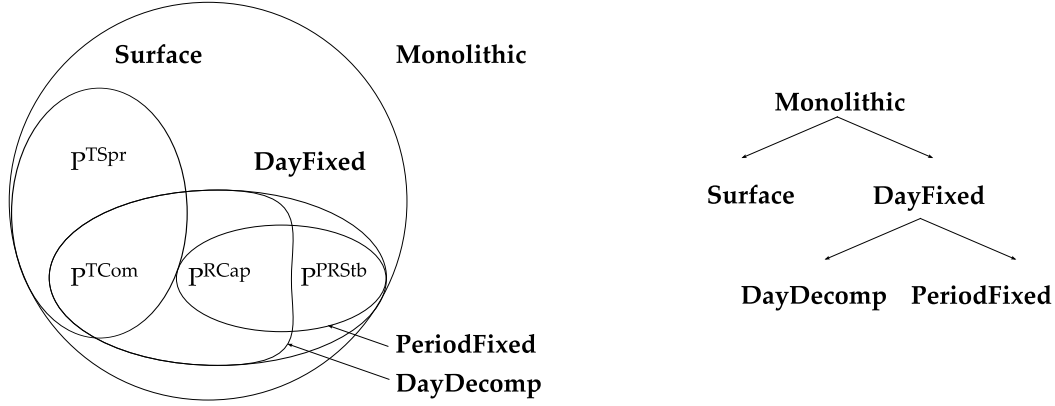


Fig. 6. A schematic illustration of the penalties considered in the formulations we use: **Monolithic** uses the complete objective function, **Surface** sets  $W^{RCap} = W^{RStb} = 0$ , **DayFixed** has  $P^{TSpr}$  fixed, **PeriodFixed** has  $P^{TSpr}$  and  $P^{TCom}$  fixed, and **DayDecomp** has  $P^{TSpr}$  fixed and  $W^{RStb} = 0$ .

the relaxation either in the surface component or within a dive being cut by factor of more than two thousand, compared to the “monolithic” formulation.

#### 4.1 Objective-restricted Submodels

One could consider generating reduced problems by setting any subset of the weights to zero. With four penalties, there are  $2^4 - 1 = 15$  possible non-trivial choices. However, we only use the following problem:

- **Surface:** We set  $W^{RCap} = W^{RStb} = 0$  so that room over-filling and room stability are not considered. Since no explicit room assignments are required, there can be much fewer variables. We will see later that the ternary variables  $x_{p,r,c}$  are no longer required, which gives us much shorter run-times of the linear programming solver. (See Table 4.) However, we add extra constraints that bound the number of rooms used in any single period; they impose that there will always be enough rooms for courses at each period, and so guarantee that a surface solution can always be extended by the dive to a feasible solution to the full problem. However, these extra constraints convert the colouring to bounded colouring and make solving the “surface” search harder, both in theory and practice.

The sets of the objectives considered by each formulation are illustrated in Figure 6. This also serves to emphasise the crucial point that the methods we use are intended for the case of multiple terms in the objective, or equiv-

alently, for multiple classes of relatively-complex soft constraints.

One can reasonably ask why we use this particular split between surface and dive models. Firstly, the graph colouring component is important in the instances under consideration. In Table 1, we can see that the ratio of events to available room slots is typically 60-90% which is quite high, so it is reasonable that the bounded colouring problem is hard to solve, and so ought to be solved first. That is, the bounded colouring needs to be done at the surface level. Also, Table 2 gives optimal objective vectors for different weight vectors. (It does this for the small instance comp01 that happens to be fairly easy to solve exactly, and uses the monolithic IP formulation detailed in the previous section.) We see that the time-related penalties ( $P^{\text{TSpr}}$  and  $P^{\text{TCom}}$ ) make the largest contributions to the final objective, and so it is natural to address these first. Limited experimentation has been conducted with solvers where  $W^{\text{RCap}} = W^{\text{RStb}} = W^{\text{TCom}} = 0$ . As is suggested by Table 2, the solver at the surface is not considerably faster, when only automatic reductions are considered. Rather surprisingly, the solver is not considerably faster, however, even when non-automatic reformulations are applied, and these gains do not offset the need to spend more time diving. (See Section 5.2.) There are also alternatives exploiting interchangeable rooms.

#### 4.2 Exploiting Interchangeable Rooms: “Multi-rooms”

Suppose that we have two rooms of exactly the same size. Then the only way that the rooms are not interchangeable is because of the room stability constraint. If we take a solution and swap the rooms at any single time period then no constraints are broken and no objectives affected, except potentially the room stability. Hence, if we are using a formulation, such as the surface, that does not care about room stability, then we can treat the rooms as interchangeable. Thus, we could replace the 2 standard rooms with a single room with multiplicity, which we call a “multi-room”.

A multi-room of size “ $(m,a)$ ” will have multiplicity  $m$ , capacity  $a$ , and will function exactly as  $m$  separate indistinguishable rooms. That is: It can accommodate  $m$  separate events of sizes up to  $a$  each, without any overflow. This mild extension is straightforward, but has the advantage that we then have the option to replace the  $r$  index of the  $x_{p,r,c}$  variables by an index into a set of multi-rooms. Any solution using multi-rooms can be translated into constraints on original rooms that define a neighbourhood in the full problem. Within this neighbourhood, there will always be a feasible solution, and we can easily find the one minimising  $P^{\text{RStb}}$ , the penalty for “room stability”.

Here we use multi-rooms only as a device to reduce the number of variables and remove symmetries that would enlarge the search space. However, it is also reasonable that multi-rooms could be directly useful. Specifically, in practice, the room stability might well not be quite so strict as the Udine timetabling instances demand. In some teaching facilities, there could well be a suite of teaching rooms that are all of the same size, with the same facilities, and which are located very close to each other. In such a case, it could well be that there really would be no need for a room stability penalty for mixed use. In this case, they could well be treated exactly as a single multi-room with appropriate multiplicity.

Generally, only a few rooms do have exactly the same sizes. However, it is often the case that there are many rooms of roughly the same size. To exploit this situation, note that if we join two rooms of different sizes into a single multi-room then it can affect the room capacity objective, but again it will *not* affect the hard constraints. Hence, we do allow the creation of relaxations in which various sets of rooms are joined into associated multi-rooms with capacity the size of the largest original room. Specifically, if we select a set of multi-rooms with capacities  $\{c_i | i = 1 \dots |R|\}$  then we can replace them with a multi-room of size  $(m, \max c_i)$ . An intermediate case would be to divide the rooms into two multi-rooms, according to whether they are smaller or not than some selected intermediate size. We will introduce such a neighbourhood generator, denoted by **Surface2**, in Section 5.

### 4.3 Value-restricted Submodels

For the dives, we use value-restricted submodels of the **Monolithic** model. Two pure value-restricted submodels are defined by restricting the times of courses based on the solution obtained at the surface level:

- **PeriodFixed** dives: The periods of all the courses are fixed to be the same as obtained from the surface solution.
- **DayFixed** dives: The days of all the courses are fixed, but not the explicit period within the day. That is, for each course the assigned “period” is relaxed to just give a day assignment.

In both pure value-restricted subproblems, the spread of events of a course over distinct week-days is entirely fixed, and  $W^{TSpr}$  hence becomes irrelevant. **PeriodFixed** dives also fix time compactness penalty  $P^{TCom}$ , and thus only room assignment remains to be found, minimising the room related penalties ( $P^{RCap}$  and  $P^{RStb}$ ). In **DayFixed** dives, the compactness penalty  $P^{TCom}$  can still potentially be improved. A middle ground between these two approaches is offered by value- and objective-restricted submodels.

#### 4.4 Value- and Objective-restricted Submodels

Two obvious value- and objective-restricted submodels can be defined by restricting the times of courses based on the solution obtained at the surface level, and not considering  $P^{\text{RStb}}$  or by forcing  $P^{\text{RStb}}$  to zero:

- **DayDecomp** dives:  $P^{\text{RStb}}$  is not considered and the days of all the courses are fixed, but not the explicit period within the day. That is, for each course, the assigned “period” is relaxed to just give a day assignment and the lowest possible penalty for time compactness and room capacity is sought.
- **DayFixedZero** $P^{\text{RStb}}$  dives:  $P^{\text{RStb}}$  is forced to be zero and the days of all the courses are fixed, but not the explicit period within the day. That is, for each course, the assigned “period” is relaxed to just give a day assignment and an assignment with zero penalty for room stability is sought.

These two value- and objective-restricted submodels have the advantage that they reduce the links between variables representing individual days, which translates into matrices closer to the block structure and improvements in the performance of the diving integer programming solver. Many other subproblems, most notably variants of **PeriodFixed** and **DayFixed** dives using stochastic ruining (Schrimpf et al., 2000; Dueck et al., 2002), are of course possible, but are not studied here. Some experience with implementing and testing the presented alternatives empirically is described in Section 7.

#### 4.5 Control Strategies

Finally, we have designed both **Anytime** and **Contract** control strategies for Udine Course Timetabling, using **PeriodFixed** dives followed by **DayFixed** dives. The details of their functioning is outlined in Figure 7. **Contract** algorithms turned out to perform better, as expected, especially when multiple solutions can be found at **Surface** within the given time limit. The only difficulty seems to be the choice of the partition of short time limits between **Surface** and dives in **Contract** algorithms. When a time limit is given, and is not too strict, however, there seem to be no reasons to use **Anytime** strategies.

```

class AnytimeStrategy implementing Strategy:
  constructor(config):
    keep track of config
    initialise bestSoFar to an error value
  onFeasibleSolution():
    foreach type in config.getDiveTypes():
      if time > config.getAnytimeDivingOnset(type):
        Neighbourhood def = getNeighbourhood(type)
        update bestSoFar with
          dive(def, config.getDiveTimeLimit(type))
  onTimeout():
    return bestSoFar

class ContractStrategy implementing Strategy:
  constructor(config):
    keep track of config
    initialise a stack of neighbourhoods n[t]
    for each t in config.getDiveTypes()
  onFeasibleSolution():
    foreach type in config.getDiveTypes():
      fixDayNeighbs.push(getNeighbourhood(type))
  onTimeout():
    initialise bestSoFar to an error value
    foreach type in config.getDiveTypes():
      c = 0
      while time > config.getTimelimit() &&
        ! n[type].empty() && c < config.getRunLimit(type):
        update bestSoFar with
          dive(n[type].pop(), config.getDiveTimeLimit(type))
      c += 1

class SampleAnytimeSolver():
  solve():
    config.setDiveTypes([FixPeriod, FixDay])
    foreach type in config.getDiveTypes():
      come up with a suitable time limit for type
      config.setDiveTimeLimit(type, limit)
    load an instance
    initialise a solver for Surface, instance, and config
    install AnytimeStrategy(config) as a solver callback
    try solving Surface

class SampleContractSolver():
  solve(timeLimit):
    config.setTimeLimit(timeLimit)
    config.setDiveTypes([FixPeriod, FixDay])
    config.setDiveTimeLimit(FixPeriod, timeLimit/50)
    config.setDiveTimeLimit(FixDay, timeLimit/5)
    foreach type in config.getDiveTypes():
      config.setRunLimit(type, 3)
    load an instance
    initialise a solver for Surface, instance, and config
    install ContractStrategy(config) as a solver callback
    try solving Surface for timeLimit/3

```

Fig. 7. Pseudocode of the control strategies in use

## 5 Non-Automatic Re-Formulations of the Subproblems

As has been described in Section 3, at the “surface” level of the heuristic for Udine Course Timetabling, there is an objective-restricted neighbourhood generator trying to find an assignment of events to periods, such that

at most a given number of events takes place at any given period, but disregarding other issues of assignment of rooms, such as room capacities. Feasible solutions of the assignment of events to periods are relaxed into value-restricted neighbourhoods given by the assignment of events to days or periods. It would obviously be possible to use the monolithic formulation with weights  $(W^{\text{RCap}} W^{\text{TSpr}} W^{\text{TCom}} W^{\text{RStb}}) = (0, 5, 2, 0)$  at the “surface” level, and to rely on the automatic pre-solving routines in a modern integer programming solver. As will be shown in Section 7, however, improvements in the run-time of the linear programming solver, which determine the run-time of the integer programming solver, of several orders of magnitude can be achieved by non-automatic reformulation.

### 5.1 The Search for Good Neighbourhoods

In the formulation that we denote as **Surface**, the “core” decision variables  $w$  are accompanied by dependent variables  $v$ ,  $q$ , and  $z$ , introduced previously:

- $w$  are binary decision variables indexed with periods and courses. Their values are constrained so that in any feasible solution, course  $c$  should be taught at period  $p$ , if and only if  $w_{p,c}$  is set to one.

The objective function can be expressed as:

$$\min W^{\text{TCom}} \sum_{u \in U} \sum_{d \in D} \sum_{s \in Z} z_{u,d,s} + W^{\text{TSpr}} \sum_{c \in C} q_c$$

Hard constraints can be formulated similarly to those in **Monolithic**:

$$\forall c \in C \quad \sum_{p \in P} w_{p,c} = E^c \quad (25)$$

$$\forall p \in P \forall u \in U \quad \sum_{c \in \tilde{U}^u} w_{p,c} \leq 1 \quad (26)$$

$$\forall p \in P \forall t \in T \quad \sum_{c \in \tilde{T}^t} w_{p,c} \leq 1 \quad (27)$$

$$\forall p \in P \quad \sum_{c \in C} w_{p,c} \leq |R| \quad (28)$$

$$\forall \langle c, p \rangle \in N \quad w_{p,c} = 0 \quad (29)$$

Notice that constraint (28) is the only mention of rooms in this formulation of neighbourhood definition. It makes the number of rooms used in any period smaller than  $|R|$ , which corresponds to making the colouring bounded. It would be possible, for example, to constrain the number of large courses taught in any one period to be less than the number of large rooms, with



suitable definitions of “large”. Similar constraints, however, do not seem to improve the quality of neighbourhoods significantly.

By minor changes of constraints (7–9) in the monolithic formulation, the array  $q$  can be constrained using:

$$\forall c \in C \forall d \in D \forall p \in \tilde{D}^d \quad w_{p,c} \leq v_{c,d} \quad (30)$$

$$\forall c \in C \forall d \in D \quad \sum_{p \in \tilde{D}^d} w_{p,c} \geq v_{c,d} \quad (31)$$

$$\forall c \in C \quad \sum_{d \in D} v_{c,d} \geq Q^c - q_c \quad (32)$$

Inequalities 30 and 31 in effect aggregate values from  $w$  into  $v$ . Inequality 32 then calculates the number of days the instruction is short of the recommended value in  $Q$ .

Patterns can be penalised again using the natural formulation, used already in constraints (10–13) in the monolithic model. For instances with four periods per day, we obtain:

$$\forall u \in U \ d \in D \ \forall \langle p_1, p_2, p_3, p_4 \rangle \in \tilde{D}^d \sum_{c \in \tilde{U}^u} (w_{p_1,c} - w_{p_2,c}) \leq z_{u,d,1} \quad (33)$$

$$\forall u \in U \ d \in D \ \forall \langle p_1, p_2, p_3, p_4 \rangle \in \tilde{D}^d \sum_{c \in \tilde{U}^u} (w_{p_4,c} - w_{p_3,c}) \leq z_{u,d,2} \quad (34)$$

$$\forall u \in U \ d \in D \ \forall \langle p_1, p_2, p_3, p_4 \rangle \in \tilde{D}^d \sum_{c \in \tilde{U}^u} (w_{p_2,c} - w_{p_1,c} - w_{p_3,c}) \leq z_{u,d,3} \quad (35)$$

$$\forall u \in U \ d \in D \ \forall \langle p_1, p_2, p_3, p_4 \rangle \in \tilde{D}^d \sum_{c \in \tilde{U}^u} (w_{p_3,c} - w_{p_2,c} - w_{p_4,c}) \leq z_{u,d,4} \quad (36)$$

This formulation of **Surface** can obviously also be strengthened by addition of cuts, as described by [Burke et al. \(2008a\)](#).

## 5.2 Better Neighbourhoods?

The approach outlined above is not the only possible neighbourhood generator, although the range of possible formulations is somewhat limited by the choice of decision variables. Considering further soft constraints would necessitate the addition of a considerable number of variables, resulting in very slow LP relaxations. (See Table 4 for an illustration of the effect and Section 7 for discussion.) Replacing the array  $w$  with an array indexed with courses and days would make it impossible to implement the graph colouring component. The only option left, hence, seems to be the consideration of only a single soft constraints, setting  $(W^{\text{RCap}} \ W^{\text{TSpr}} \ W^{\text{TCom}} \ W^{\text{RStb}}) =$

$(0, 5, 0, 0)$ . This enables the removal of  $z$  and constraints (33–36). It seems, however, that using weights  $W = (0, 5, 0, 0)$  makes it necessary to search larger neighbourhoods in dives (see below for **DayFixed**), and results in worse performance on both short and long runs. Alternatively, we can exploit interchangeable rooms.

As has been suggested in Section 4, **Surface** can be thought of as the extreme case of room aggregation, in which all the  $|R|$  rooms are joined into a single multi-room of multiplicity  $|R|$  and capacity the size of the largest room. In all these instances, the resulting capacity is always larger than the largest event, and so the multi-room multiplicity just gives the bound on the number of events per time-slot. An intermediate case would be to divide the rooms into two multi-rooms, according to whether they are smaller or not than some selected intermediate size. In a neighbourhood generator denoted **Surface2**, the threshold room size is just taken to be the median of all the room sizes. This keeps the number of variables down, but still adds some restrictions so that larger events are likely to be evenly spread out over the periods.

More formally, given the set  $M$  of pairs  $(m, a)$ , representing multiplicity and capacity of a multi-room, the formulation we denote **Surface2** uses the “core” decision variables  $x'$ , which differ from  $x$  only in that they are indexed with  $M$  instead of  $R$ , together with dependent variables  $v$ ,  $q$ , and  $z$ , introduced previously, and together with  $y'$ , which are similar to  $y$ , only indexed with  $M$  instead of  $R$ . The objective function can be expressed as:

$$\begin{aligned} \min \quad & W^{\text{RCap}} \sum_{(m,a) \in M} \sum_{p \in P} \sum_{\substack{c \in C \\ S^c > a}} x'_{p,(m,a),c} (S^c - a) + W^{\text{TCom}} \sum_{u \in U} \sum_{d \in D} \sum_{s \in Z} z_{u,d,s} \\ & + W^{\text{TSpr}} \sum_{c \in C} q_c + W^{\text{RStb}} \sum_{c \in C} \left( \left( \sum_{r \in M} y'_{r,c} \right) - 1 \right) \end{aligned}$$

Hard constraints can also be formulated similarly to those in **Monolithic**

(1–5):

$$\forall c \in C \quad \sum_{p \in P} \sum_{r \in M} x_{p,r,c} = E^c \quad (37)$$

$$\forall p \in P \forall (m, a) \in M \quad \sum_{c \in C} x_{p,r,c} \leq m \quad (38)$$

$$\forall p \in P \forall c \in C \quad \sum_{r \in M} x_{p,r,c} \leq 1 \quad (39)$$

$$\forall p \in P \forall t \in T \quad \sum_{r \in M} \sum_{c \in \tilde{T}^t} x_{p,r,c} \leq 1 \quad (40)$$

$$\forall p \in P \forall u \in U \quad \sum_{r \in M} \sum_{c \in \tilde{U}^u} x_{p,r,c} \leq 1 \quad (41)$$

$$\forall \langle c, p \rangle \in N \quad \sum_{r \in M} x_{p,r,c} = 0 \quad (42)$$

The remaining constraints of **Monolithic** can be used in **Surface2**, when  $x'$  replaces  $x$ ,  $y'$  replaces  $y$ , and  $M$  replaces  $R$ .

### 5.3 The Diving

When an integer feasible solution is found at **Surface**, it waits to be translated to a solution of the Udine Course Timetabling Problem. There are at least two obvious restrictions of the monolithic formulation, which we refer to as **PeriodFixed** and **DayFixed** dives in Section 3. It is clearly possible to constraint the monolithic formulation into a **PeriodFixed** dive by the addition of constraints:

$$\forall c \in C \forall p \in P \quad \sum_{r \in R} x_{p,r,c} = w_{p,c} \quad (43)$$

On the instances from the International Timetabling Competition 2007, it is often possible to find optima for **PeriodFixed** dives within seconds. As will be described in Section 7, however, the quality of solutions obtained this way varies widely from neighbourhood to neighbourhood.

Alternatively, it is possible to dive into neighbourhoods defined by assignment of courses to days. In order to do so, values of the array  $D$  indexed with courses and days are pre-computed outside of the solver as:

$$\forall p \in P \forall d \in D \quad D^{d,c} = \sum_{p \in \tilde{D}^d} w_{p,c}$$

Then, it is possible to constraint the monolithic formulation using

$$\forall c \in C \forall d \in D \forall p \in \tilde{D}^d \quad \sum_{r \in R} x_{p,r,c} = D^{d,c} \quad (44)$$

Presolving routines of modern general purpose integer programming solvers are typically able to shrink integer programming instances obtained in **Day-Fixed** dives by the factor of ten or more. Subsequently, optima within such neighbourhoods are found within minutes for the instances from the International Timetabling Competition. For details, see Section 7.

#### 5.4 *Why Not Better Diving?*

A middle ground between these two solutions is represented by “ruining” (Schrimpf et al., 2000) into the assignment of events to days only those elements  $w$ , which seem to contribute to the objective function, or to its factor  $P^{\text{TCom}}$ . The first option is easy to implement, as modern integer programming solvers expose the pseudo-cost of individual variables, but it does not seem to be particularly useful for instances from the International Timetabling Competition 2007. The implementation of the second option involves a certain computational effort, but it might prove useful in some instances. Both kinds of “alternative dives” are disregarded in the remainder of the paper, and might be the focus of future work.

Table 2

The effects of disabling various subsets of soft constraints by setting the corresponding weights in the monolithic model to zero on CPLEX 10 run-time for instance comp01. Only the default in-built pre-processing and cuts are used and only the best feasible solution obtained within one hour per run is presented. Notice that when a weight is set to zero, the associated penalty is typically high.

$W^{RCap}$	$W^{TSpr}$	$W^{TCom}$	$W^{RStb}$	LP Matrix	Barrier LP Runtime	Node with last feas. sol.	Default IP Runtime	$p^{RCap}$	$p^{TSpr}$	$p^{TCom}$	$p^{RStb}$	Obj.
0	0	0	0	$6639 \times 5407$	44.08 s	0	66 s	2294	30	350	93	0
0	0	0	1	$6639 \times 5407$	43.66 s	370	1066 s	2706	30	350	0	0
0	0	2	0	$7059 \times 5757$	61.24 s	140	884 s	2107	30	0	77	0
0	5	0	0	$6665 \times 5435$	40.44 s	0	148 s	2387	0	350	92	0
1	0	0	0	$6639 \times 5407$	21.68 s	0	62 s	4	30	350	44	4
0	0	2	1	$7059 \times 5757$	67.73 s	617	1033 s	2874	30	0	0	0
0	5	0	1	$6665 \times 5435$	39.41 s	402	1554 s	2023	0	350	0	0
0	5	2	0	$7085 \times 5785$	66.18 s	90	881 s	2365	0	0	78	0
1	0	0	1	$6639 \times 5407$	9.97 s	180	521 s	4	30	350	1	5
1	0	2	0	$7059 \times 5757$	21.21 s	124	518 s	4	30	0	31	4
1	5	0	0	$6665 \times 5435$	10.01 s	0	52 s	4	0	350	44	4
0	5	2	1	$7085 \times 5785$	39.50 s	1964	1050 s	1672	0	0	0	0
1	0	2	1	$7059 \times 5757$	21.40 s	487	1416 s	4	30	0	1	5
1	5	0	1	$6665 \times 5435$	7.96 s	269	651 s	4	0	350	1	5
1	5	2	0	$7085 \times 5785$	22.35 s	145	395 s	4	0	0	43	4

Table 3

The effects of varying the weight  $W^{TSpr}$  on CPLEX 10 run-time for the monolithic model and instance comp01.

$W^{RCap}$	$W^{TSpr}$	$W^{TCom}$	$W^{RStb}$	LP Matrix	Barrier LP Runtime	Node with last feas. sol.	Default IP Runtime	$p^{RCap}$	$p^{TSpr}$	$p^{TCom}$	$p^{RStb}$	Obj.
1	2	2	1	$7085 \times 5785$	19.19 s	1053	1205 s	4	0	0	1	1
1	4	2	1	$7085 \times 5785$	19.19 s	405	> 3600 s	4	0	0	2	(6)
1	8	2	1	$7085 \times 5785$	19.49 s	1420	> 3600 s	5	0	0	1	(6)
1	16	2	1	$7085 \times 5785$	19.23 s	4822	> 3600 s	4	0	0	2	(6)
1	32	2	1	$7085 \times 5785$	19.06 s	586	> 3600 s	4	0	0	2	(6)
1	64	2	1	$7085 \times 5785$	19.39 s	3803	2387 s	4	0	0	1	5

## 6 Related Research Issues: A Brief Discussion

It should be noted that the components of this approach draw upon a rich history of work in this area. Decompositions have been used in integer programming for a long time ([Ralphs and Galati, 2006](#), provide a survey) and the effects of non-automatic reformulations are also well known ([Williams, 1978](#); [Barnhart et al., 1993](#), for example). In the timetabling community, the “times first, rooms second” decomposition is a standard procedure. See [Burke and Newall \(1999\)](#) for references. Decompositions using integer programming are less common, although [Lawrie \(1969\)](#), for instance, used a form of column generation as early as 1969. Decompositions providing lower bounds are yet less common, and often limited in constraints they allow. [Carter \(1989\)](#) used only variables indexed with rooms and courses, which prohibits formulation of period-related soft constraints, but imposes a variant of room stability via cuts. More recently, [Daskalaki et al. \(2005\)](#) used “times first, rooms second” with integer programming models solved at both stages, although, in our terms, they use only a single type of dives, anytime control strategy, and evaluate the performance only on two small instances. Yet more recently, [Lach and Lübbecke \(2008a\)](#) have also developed a similar approach, independently of the present authors.<sup>2</sup> They use a rather different and interesting surface component, based on their studies of the Partial Transversal Polytope ([Lach and Lübbecke, 2008b](#)). Their very respectable results are discussed below, in Section 7, and are included in Figure 8 for comparison. In machine scheduling, such approaches are often termed “machine aggregation heuristics” [Leung et al. \(2004\)](#) and it is not too difficult to translate rooms to machines and vice versa. We have, however, been unable to find a more general two-staged decomposition methodology using integer programming at both stages, comparable to the one presented here. Overall, we heartily recommend both papers on decompositions of timetabling ([Daskalaki et al., 2005](#); [Lach and Lübbecke, 2008a](#)) to the reader, for comparison.

Multiphase exploitation of multiple objective-/value-restricted submodels in some aspects resembles very large neighbourhood search ([Ahuja et al., 2002](#)) and adaptive large neighbourhood search ([Røpke and Pisinger, 2006](#)): We use a number of different subproblems, which can be very large and slow to solve. Multiple and/or large neighbourhoods have recently been very popular in local search solvers for timetabling applications. [Di Gaspero and Schaerf \(2003\)](#) and [Müller \(2008\)](#), for instance, use multiple polynomial-

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<sup>2</sup> Results of [Lach and Lübbecke \(2008a\)](#) were first submitted in February 2008 to Practice and Theory of Automated Timetabling, a conference held in Montréal, Canada, in August 2008. The approach of the present authors was first presented at the Mixed Integer Programming Workshop in August 2007.



time searchable neighbourhoods for Udine Course Timetabling. [Abdullah et al. \(2006, 2007\)](#) and [Meyers and Orlin \(2006\)](#) have proposed large neighbourhoods for timetabling, without using integer programming to search the them. [Daskalaki et al. \(2005\)](#) searches large neighbourhoods using integer programming. [Avella et al. \(2007\)](#) study high-school timetabling problem and do a form of “value-restricted diving” based on fixing the schedule for all but two teachers. Depending on the particular problem and implementation, however, the “surface” component in our approach tends to produce only few progressively improving solutions, and good lower bounds valid for the full problem, which is often not the case in general large neighbourhood search. In contrast to large neighbourhood search, the “dives” also do not have to be explored at the time of their discovery or even in the order of discovery, or even on the same machine. If it is possible to produce a number of progressively improving solutions at the surface, it indeed seems natural to start diving in neighbourhoods from the best solution found at the surface, with the hope that the solutions found within the dive can be used to cut off exploration of other dives once their lower bounds are known. Very large neighbourhood search nevertheless remains the metaheuristic approach closest to the presented one.

There are also some similarities with the concept of “ruin-and-recreate” ([Schrimpf et al., 2000](#); [Dueck et al., 2002](#)). As [Lin \(1965\)](#) pointed out, the key decision is which elements to preserve and which to relax, when the solution is passed from the surface to a dive. This might be termed an option to ruin part of the solution before diving. However, it should be emphasised that the overall algorithm is very different from “ruin-and-recreate”. In particular there is no overall loop in which solutions are recycled. A distinguishing feature of our approach is that the flow of solutions, as given in [Figure 3](#), is different from the usual cycle of solutions. More specifically, in [Figure 3](#), there is no arrow returning from the dive to the surface level. The surface merely continues to produce its next solution, without reusing the result of the dive directly. If the present-best solution is found in a dive, its value only provides an upper bound (cut-off limit) for further dives. This strategy seems much more compatible with the architecture of integer programming solvers.

There are also connections to column generation and dimensionality reduction in multiobjective optimisation. The heuristic surface-dive decomposition can be likened to column generation and other exact decompositions studied in integer programming ([Ralphs and Galati, 2006](#)). The “surface” and “dive” components could also be thought of as an biobjective integer program. Although there has been recently some progress in the study of biobjective integer programs ([Ralphs et al., 2006](#)), they do not seem to yield direct performance improvements. It would also be most interesting to study the links to dimensionality reduction ([Tenenbaum et al., 2000](#)).

These connections, however, are largely yet to be established, which might take some time: As has been pointed out by [Gandibleux and Ehrgott \(2005\)](#), the progress in understanding the true multiobjective nature of many optimisation problems and related solution methods remains painfully slow.

Table 4

Linear programming relaxations for instances of the Udine Course Timetabling problem: dimensions of matrices after all default automatic reductions in CPLEX 11, root relaxation time using CPLEX 11 Dual Simplex LP solver, and the remaining “elapsed time”, after which CPLEX 11 is still at the root node of the monolithic formulation. For dives, the measurements are for the dive executed first in the given run.

Instance	Reduced LP ( <b>Monolithic</b> )		Reduced LP ( <b>Surface</b> )		Reduced LP ( <b>PeriodFixed</b> )		Reduced LP ( <b>DayFixed</b> )	
comp01	8593 × 6696	29.01 s	3807 × 2341	2.01 s	1484 × 1128	0.14 s	3984 × 4017	5.33 s
comp02	34438 × 29559	1058.47 s	8629 × 5364	9.11 s	6605 × 5840	2.80 s	8089 × 10516	16.76 s
comp03	30985 × 27240	493.43 s	7838 × 4966	5.22 s	5825 × 5136	1.92 s	7516 × 10230	19.00 s
comp04	37570 × 33195	590.15 s	8097 × 5106	1.51 s	7367 × 6570	2.29 s	8991 × 14019	19.53 s
comp05	19795 × 16652	109.08 s	9369 × 6946	9.16 s	2282 × 1827	0.04 s	5526 × 5474	2.85 s
comp06	49360 × 43485	1729.20 s	10689 × 6645	16.63 s	9361 × 8442	9.26 s	13096 × 19977	78.90 s
comp07	67901 × 60001	6489.69 s	13491 × 8108	45.05 s	12365 × 11300	13.72 s	16974 × 24940	157.06 s
comp08	39935 × 35224	899.81 s	8643 × 5434	2.63 s	8240 × 7380	6.02 s	11316 × 17657	42.66 s
comp09	36382 × 31951	653.75 s	8290 × 5333	2.19 s	7195 × 6390	3.75 s	8717 × 11881	17.58 s
comp10	51839 × 45759	2087.70 s	11244 × 6850	21.58 s	9628 × 8712	8.97 s	12388 × 20637	83.90 s
comp11	11747 × 8448	28.86 s	5699 × 3334	2.93 s	1367 × 960	0.06 s	5352 × 5896	6.56 s
comp12	32893 × 27504	480.57 s	12570 × 8724	27.25 s	3990 × 3355	0.30 s	8114 × 8342	10.84 s
comp13	39610 × 35188	771.64 s	8320 × 5329	2.33 s	8275 × 7410	4.33 s	10599 × 16795	33.44 s
comp14	37785 × 32828	866.63 s	8685 × 5333	8.10 s	6905 × 6120	2.23 s	8151 × 12674	13.19 s

Fig. 8. Our results compared against the results of [Lach and Lübbecke \(2008a\)](#) and [Müller \(2008\)](#). In all cases, CPLEX 11 is used with default parameters, no custom cuts, and CPU time normalised using the benchmark of [Di Gaspero et al. \(2007\)](#). Within 1 CPU unit, we use **Surface** and **PeriodFixed**. Within 10 or 40 CPU units, we use **Surface2** with both **PeriodFixed** and **DayFixed** dives.

Instance	Results of the proposed heuristic (using CPLEX 11)									Monolithic 40 CPU Units	
	1 CPU Unit			10 CPU Units			40 CPU Units			Obj	LB
	Obj.	LB	Gap	Obj.	LB	Gap	Obj.	LB	Gap		
comp01	168	0		10	4	60.0%	9	5	44.4%	6	4
comp02	114	0		101	0		63	1	98.4%		1
comp03	158	25	84.2%	144	33	77.1%	123	33	73.2%		25
comp04	153	35	77.1%	36	35	2.8%	36	35	2.8%		8
comp05	1447	119	91.8%	649	111	82.9%	629	114	81.9%	604	111
comp06	277	13	95.3%	317	15	95.3%	46	16	65.2%		12
comp07		6		857	6	99.3%	45	6	86.7%		0
comp08	173	37	78.6%	53	37	30.2%	41	37	9.8%		11
comp09	112	68	39.3%	115	65	43.5%	105	66	37.1%		21
comp10	70	3	95.7%	49	4	91.8%	23	4	82.6%		2
comp11	288	0		12	0		12	0		0	0
comp12		101		889	95	89.3%	785	95	87.9%		39
comp13	556	52	90.6%	92	52	43.5%	67	54	19.4%		14
comp14	123	41	66.7%	72	42	41.7%	55	42	23.6%		40
Instance	Compared to: Results of Lübbecke and Lach (using CPLEX 11)									and Müller 10x1 CPU Unit	
	1 CPU Unit			10 CPU Units			40 CPU Units			Avg	Best
	Obj.	LB	Gap	Obj.	LB	Gap	Obj.	LB	Gap		
comp01	12	4	66.7%	12	4	66.7%	12	4	66.7%	5.0	5
comp02	239	0		93	8	91.4%	46	11	76.1%	61.3	51
comp03	194	0		86	0		66	25	62.1%	94.8	84
comp04	44	22	50.0%	41	28	31.7%	38	28	26.3%	42.8	37
comp05	965	92	90.5%	468	25	94.7%	368	108	70.7%	343.5	330
comp06	395	7	98.2%	79	10	87.3%	51	10	80.4%	56.8	48
comp07	525	0		28	2	92.9%	25	6	76.0%	33.9	20
comp08	78	30	61.5%	48	34	29.2%	44	37	15.9%	46.5	41
comp09	115	37	67.8%	106	41	61.3%	99	46	53.5%	113.1	109
comp10	235	2	99.1%	44	4	90.9%	16	4	75.0%	21.3	16
comp11	7	0		7	0		7	0		0.0	0
comp12	1122	29	97.4%	657	32	95.1%	548	53	90.3%	351.6	333
comp13	98	33	66.3%	67	39	41.8%	66	41	37.9%	73.9	66
comp14	113	40	64.6%	54	41	24.1%	53	46	13.2%	61.8	59

## 7 Computational Experience

The proposed heuristic has been implemented using ILOG Concert libraries in C++ (ILOG, 2007). ILOG CPLEX 11 is used both at **Surface** and in all dives. Some tests have also been carried out using ZIB SCIP, the present-best freely available integer programming solver developed at Konrad-Zuse-Zentrum für Informationstechnik in Berlin (Achterberg, 2004); their results are available on request from the authors. The implementation has been evaluated on a single processor of a desktop PC equipped with two Intel Pentium 4 processors clocked at 3.20 GHz and with 4 GB of RAM, running Linux. To allow easier comparison with the results of Lach and Lübbecke (2008a) and entrants of the International Timetabling Competition 2007, time measurements have been normalised using the benchmark<sup>3</sup> by Di Gaspero et al. (2007). One CPU unit in Figure 8 corresponds to 780 seconds. Within the limit of 1 CPU unit, we spend 600 seconds solving **Surface** and then 180 seconds in a single **PeriodFixed** dive. Within the limit of 10 CPU units, we spend 3420 seconds solving **Surface2**, then 180 seconds in a single **PeriodFixed** dive, and then 3600 seconds in a single **DayFixed** dive. Within the limit of 40 CPU units, we spend 3 hours solving **Surface2**, limited time in a number of **PeriodFixed** dives, and 5 hours in a single **DayFixed** dive. Full source code, logs, and solution files are available from the contact author<sup>4</sup>.

Overall, the solver can produce feasible solutions and corresponding lower bounds for all instances from the International Timetabling Competition 2007 within one or two CPU units. (It is only instances comp07 and comp12 that take two CPU units.) Indeed, if some terms of the objective are ignored at **Surface**, then provided the relative weights of the other terms are not changed, the lower bound of the objective-restricted problem is also a valid lower-bound for the complete minimisation problem. However, within one CPU unit, allotted to solvers in the International Timetabling Competition 2007, the progress is limited, mostly due to the sheer size of the LP instances involved, as outlined in Table 4. The gap<sup>5</sup> often remains as large as 95 %, if any solutions are found at all. The solver nevertheless continues to make good progress, as suggested in Figure 8, and within ten and 40 CPU units produces results with gaps comparable to those of Lach and Lübbecke (2008a). Compared to the results of Müller (2008), the winner of Track 3 in the International Timetabling Competition 2007, the quality of the solutions obtained is only mediocre, no matter whether we consider the choice of the best result in ten separate runs of one CPU unit each equiva-

<sup>3</sup> <http://www.cs.qub.ac.uk/itc2007/benchmarking/>

<sup>4</sup> <http://cs.nott.ac.uk/~jxm/> (Jakub Mareček)

<sup>5</sup> The gap is calculated using the formula of ILOG, i.e.  $100(1 - LB/UB)$ , where  $LB$  is lower bound and  $UB$  is cost of the best integer feasible solution.

lent to ten CPU units, as suggested by [Lach and Lübbecke \(2008a\)](#), or not. Except for the instance comp04, comp06, and comp08, we have not been able to improve upper bounds obtained by [Müller \(2008\)](#) within 10 runs of 1 CPU unit within a single 40 CPU unit run. On comp04, however, we have closed the absolute gap to 1 (2.8%), a feat which seems rather difficult to achieve using monolithic formulations. The possibility to perform a heuristic search whilst obtaining some information about its quality, perhaps together with the ease of implementation, hence represents two of the few, and perhaps the only two significant advantages of the proposed approach over standard local search approaches. Nevertheless, it seems that, given this performance, such an approach could be well usable in practice, for example, in tightly constrained instances, where solutions delivered by local search heuristics are not good enough to accept, without proofs of their near-optimality.

### 7.1 *Remarks on the Instances of Linear Programming*

In this connection, it is also interesting to notice the properties of the linear programming relaxations involved, summarised in Table 4. Generally, instances both at **Surface** and in all dives are considerably smaller than instances of **Monolithic**, and there seem to be a number of instances (comp06, comp07), where the linear programming solver based on barrier methods is, by orders of magnitude, faster. On difficult instances, such as comp06, the run time of the linear programming solver for **Surface2** can be as much as four times as large as for **Surface**, and similarly many iterations can be performed per second later on. We do not have a good explanation for this behaviour. Compared to either **Surface** or **Surface2**, instances encountered in dives are very different. They are structurally more similar to weighted matching problems or multiple knapsack problems, often used to test integer programming solvers. **PeriodFixed** dives can often be solved to optimality within a couple of minutes on instances from the International Timetabling Competition 2007. **DayFixed** dives often produce considerably better solutions within ten minutes on easier instances, but often do not provide any feasible solutions within the first 30 minutes of the search on more difficult instances. Improving the numerical behaviour of linear programming solvers on the instances could perhaps lead to considerable improvements in performance.

## 8 Conclusions

We have proposed a hybrid metaheuristic with an application in university course timetabling with multiple soft constraints. In addition to performing well on the particular problem of Udine Course Timetabling, this metaheuristic seems to provide a good starting point for the development of solvers for a number of similar problems with soft constraints with only minor modifications, including most timetabling problems with pattern penalisation. The hybridisation we study might also be of more general interest. It is based on a mix of formulations of different sub-problems of the full problem, formulated in integer programming. The basic lesson learned is that the advantage of such hybridisation arises when the sub-problems are selected so as to have good properties that can help the integer programming solver. Specifically, the non-automatic reformulation of sub-problems is essential in order to gain full advantage. This is reminiscent of the dictum in local search, that the selection of neighbourhoods generally ought to be influenced by the issue of how effectively they can be implemented. Overall, this approach seems to present a promising direction in the development of hybrid metaheuristics.

We believe that realistic problems often have many different terms in the objectives and that often these objective terms can be quite awkward to encode in integer programming, requiring many extra variables. In this work on timetabling, we have seen an example of such ‘messy’ problems. We have seen that many different formulations, relaxations and abstractions can play a role. Furthermore, with control of their usage, results can be improved significantly with respect to direct use of the initial direct encoding. However, the number of possible ways to create relaxations and abstractions and link them together increases rapidly, and managing this can quickly become unyieldy. Hence, a long-term future goal is to provide intelligent decision support to help the user keep track of the possibilities and semi-automatically discover good combinations. Our belief is that such a system would greatly help integer programming methods to achieve good results with less time and effort spent in ‘tuning’ the combinations of encodings.

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